Under Pressure – How the Environment Affects Productivity and Efficiency of European Life Insurance Companies

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Abstract: Deregulation and widespread economic changes have fundamentally affected the business conditions of European life insurance companies over the last decades. In this paper, we apply multi-stage Data Envelopment Analysis to identify the impact of the changing environment on productivity and efficiency. Considering a sample of 960 life insurance companies from 14 European countries we show that interest rates, equity market performance and inflation are three important environmental drivers of efficiency. We also document that some companies are over-utilizing equity capital, resulting in significant efficiency losses. Our results reveal a productivity decline, but an efficiency increase in the period 2002-2013; both trends can be explained by more challenging business conditions.

1. Introduction

The 1994 deregulation of the financial services industry and widespread economic changes such as the internationalization and low interest rates signify significant competitive pressure for European life insurance markets. More competitive markets bring pressure on efficiency in the sector forcing those firms not able to adapt to state-of-the-art technology to be displaced. Moreover, bad underwriting practices are further penalized because they can no longer be compensated by high capital market returns. The observed changes in the last 20 years thus give reason to expect an increase in efficiency in the European life insurance market.

We analyze the impact of these major environmental changes on the productivity and efficiency of European life insurance companies with a new innovative measurement approach. The innovative element is that we incorporate uncontrollable variables in a multi-stage Data Envelopment Analysis (DEA), an approach that allows distinguishing the environmental changes and changes in management practices. Furthermore, we identify environmental and firm-specific drivers of efficiency in a second-stage regression analysis following Simar and Wilson (2007). Our approach enables us to identify which parts of productivity and efficiency changes are due to the environment and which aspects are due to managerial ability.

To the best of our knowledge, there is so far only one paper that considers the impact of uncontrollable variables on efficiency in an insurance context. Huang and Eling (2013) analyze the efficiency of non-life insurance companies in the BRIC (Brazil, Russia, India, China) countries and document that the environment strongly affects the efficiency of non-life insurers operating in these countries. We built upon and expand their analysis by an analysis of the life insurance sector and by a consideration of the European marketplace.

In our empirical analysis we consider three research questions: First, how does the operating environment affect life insurers efficiency? We expect that especially the capital markets are one of the main drivers of efficiency in the life insurance sector. Second, we are interested in the interaction between the operating environment and firm-specific characteristics. How do firm-specific characteristics such as size, ownership form or solvency impact efficiency before and after controlling for the operating environment? Third, how does productivity and efficiency of the European life insurance sector develop over time? Given the increasingly different business environment, we expect productivity to decline and efficiency to increase over our sample period.

To answer these three research questions, we analyze 960 life insurance companies (6'657 firm years) from 14 European countries for the years 2002-2013, which makes this paper one of the largest empirical analysis ever done on life insurance. Our findings can be summarized as follows: We show that interest rates, equity market performance and inflation are three important environmental drivers of efficiency. We document that on average larger companies and mutual insurers are more efficient than smaller companies and stock insurers; Moreover, some insurers are over-utilizing equity capital, resulting in significant efficiency losses. Finally, we show that the challenging business conditions lead productivity to decline and efficiency to increase over the sample period.

Our findings are useful for insurance managers, regulators and policymakers to enhance the understanding of the driving forces behind productivity and efficiency of the European life insurance sector. The results are useful to separate productivity and efficiency effects which are due to changes in the business environment and those which are due to managerial improvements. The findings are relevant also for other jurisdictions outside Europe and other fields such as banking which are also exposed to the same operating challenges as European life insurers.

The remainder of the paper is organized as follows. In Section 2 we discuss the theoretical background and our hypotheses. Then, in Section 3 the methodology and data are presented. Section 4 presents the empirical results and, finally, we conclude in Section 5.

2. Background and Hypotheses

Traditionally, efficiency studies implicitly assume that inefficiency is caused by bad management and occurs under identical environmental conditions (Yang and Pollitt, 2009). However, in a cross-country setting this assumption should be questioned, since the management has control only over factors internal to production, while the environment is not under its control. If the impact of uncontrollable variables is not considered, the efficiency of DMUs in an adverse external environment could be underestimated. We incorporate this aspect by using multi-stage data envelopment analysis (DEA). The consideration of uncontrollable variables in estimation is widespread in banking (see, e.g., Dietsch and Lozano-Vivas, 2000; Lozano-Vivas et al., 2002; Fries and Taci, 2005; Liu and Tone, 2008), while in insurance its application is limited to one paper from the non-life sector (Huang and Eling, 2013). Our study is thus the first to apply this methodology in a life insurance context.

Theory offers limited guidelines which determinants are important for explaining the operating environment of the life insurance industry in different countries. For this reason, the derivation of hypothesis and selection of variables relies on previous empirical studies (see Lozano-Vivas et al., 2002, for a comparable discussion in the banking sector). We consider two central dimensions constituting the operating environment of life insurers, that are macro-economic conditions and industry-specifics (see Huang and Eling, 2013 or Dietsch and Lozano-Vivas, 2000 for a similar approach). Both for the macro-economic conditions and the industry-specifics we analyze two main components in detail (see Dietsch and Lozano-Vivas, 2000; Lozano-Vivas et al., 2002), two of which have already been analyzed in existing insurance literature, while the other two – to our knowledge – have not yet been analyzed.[1] In the following we discuss the theoretic relation between each environmental dimension and efficiency, present extant empirical evidence (if it exists) and consequently formulate our

[1] In the empirical part we also control for other environmental characteristics (inflation, equity market

hypotheses (see Table 1 for an overview).

Table 1 Hypotheses and Extant Literature

Hypothesis	Specification	Extant Insurance Literature
H1: *Economic performance*	Positive relation between GDP per capita and efficiency.	Not yet analyzed in existing literature
H2: *Interest rate level*	Negative relation between interest rate level and efficiency.	Not yet analyzed in existing literature
H3: *Competition*	Positive relation between competition and efficiency.	Fenn et al. (2008); Bikker and van Leuvensteijn (2008); Choi and Weiss (2005); Berry-Stoelzle et al. (2011)
H4: *Regulation*	Positive relation between solvency regulation (i.e. capital adequacy) and efficiency.	Rees and Kessner (1999); Hussels and Ward (2007); Eling and Luhnen (2010) Luhnen (2009)

Economic performance

Various authors (Dietsch and Lozano-Vivas, 2000; Lozano-Vivas et al., 2002; Kasman and Yildirim, 2006) emphasize the importance of macro-economic factors as environmental constituents for banking efficiency. Countries with favorable conditions, e.g. high income per capita, are assumed to have a more mature banking sector, resulting in lower prices and profit margins (see e.g. Dietsch and Lozano-Vivas, 2000). While in growing markets and under expansive demand conditions, companies feel less pressured to control their costs, there is greater pressure to engage in productivity enhancing activities (e.g. cost saving programs) if the market is mature and demand conditions are strict (see e.g. Maudos et al., 2002).[2] We thus expect a positive link between GDP per capita and efficiency (Hypothesis H1).

Interest rate level

The interest income constitutes one of the main profit sources of life insurance companies, given that the majority of their funds are invested in interest bearing instruments. Over decades a common strategy of life insurers was to buy safe bonds with long-term maturity and

performance, unemployment rates), for which we do not formulate own hypotheses.

[2] Macro-economic conditions influence a variety of factors related to the demand and supply side (see e.g. Semih Yildirim and Philippatos, 2007). A variety of studies (see e.g. Fortune, 1973; Headen and Lee, 1974; Enz, 2000; Zietz, 2003) have examined the relation between macro-economic factors and life insurance demand. Note that the link between the macro-economic development and demand should be positive, but it might be linear or non-linear (see, e.g., the s-curve in Enz. 2000). Jahromi and Goudarzi (2014) show that in the long-run there is a causal relation between GDP per capita and insurance penetration ratio (one measure for insurance market maturity).

relatively high interest rates.[3] In a high interest rate environment, there is a relatively high degree of freedom since bad underwriting and higher costs can be compensated by interest income. In a low interest rate environment, however, insurance companies have to be very strict in their underwriting and cost management, since bad underwriting and inefficient cost structures can no longer be compensated by high capital market returns. We thus expect a negative link between the interest rate level and efficiency (Hypothesis 2).

Competition

The contributions of Leibenstein (1966) and Demsetz (1973) provide theoretic foundations for the relation between competition and firm efficiency. Leibenstein (1966) argues that X-inefficiencies (i.e. firms do not exploit full efficiency potential) might exist due to less motivational force. Sparse competitive pressure can evoke such a lack of motivation or, in other words, more competitive pressure could enhance efficiency.[4] A reverse relation between efficiency and competition, however, can be inferred from Demsetz (1973). He defines the efficient-structure hypothesis which argues that firms' efficiency determines the structure of the market they operate in. Because more cost efficient firms can charge lower prices they can gain more market shares. This, in contrast to the Leibenstein's theory, implies a negative relation between competition and efficiency (see e.g. Fenn et al., 2008).[5]

Divergent empirical evidence supporting both theories can be found for the insurance industry. Bikker and van Leuvensteijn (2008) document for the Dutch life insurance high levels of X-inefficiency and regard this as consequence of insufficient competition. Furthermore, Fenn

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3 This previously common strategy is becoming problematic given the low interest rate environment since long-term investments that come to term have to be replaced by bonds carrying much lower interest rates. Against this background, the minimum interest rate guarantee and further product options, which are especially prevalent in life insurance contracts, are difficult to maintain. Carson et al. (2008) and Swiss Re (2012) document the interest rate sensitivity of life insurers. Eling and Kochanski (2013) discuss the importance of interest rates for profitability of life insurers.

4 Fenn et al. (2008) call this a challenge-response mechanism where competition reduces X-inefficiencies in two ways. First, managers have the incentive to avoid personal costs resulting from a corporation's insolvency. Second, entrances of new firms allow mutual performance comparisons among all competitors.

5 This is because allocating more market shares to few (i.e. the most efficient ones) firms presumably increases

et al. (2008) find evidence for increases in X-inefficiencies in the European life insurance sector. In line with documented increases in seller concentration levels of Western and Central European markets (e.g. France, Germany, Netherlands, United Kingdom) a decline in competitive pressure can be associated with this trend. On the contrary, Choi and Weiss (2005) find evidence in favor of the efficient-structure hypothesis for the U.S. property/liability insurance market. Also, Berry-Stoelzle et al. (2011) support the efficient-structure hypothesis in the European property-liability insurance market. Based on the competing theoretic foundations and these divergent results the relation between competition and insurer efficiency is ambiguous. However, we follow the empirical results for the European life insurance sector and expect a positive relation between competition and efficiency (Hypothesis H3).

Regulation (Capital Adequacy)

Regulation in the insurance sector is mainly concerned with avoiding insolvencies; as done in other studies we consider the industry average of equity to assets as indicator of capital adequacy (see e.g. Huang and Eling, 2013 for insurance; Dietsch and Lozano-Vivas, 2000 for banking). Increased security levels associated with higher equity to asset ratios comes at the expense of costly equity capital.[6] Because equity capital is one of the inputs in efficiency measurement, an increase in equity, reflected in an increase of solvency ratios, ceteris paribus leads to a reduction in productivity; if the increase in equity applies to the entire industry, however, the impact on efficiency is not trivial.[7]

Bankruptcy is a competitive mechanism which forces inefficient firms to leave the market (Rees and Kessner, 1999). Hence, also in the absence of solvency regulation the risk of

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seller concentration levels which are associated with a lack of competition (see e.g. Nathan and Neave, 1989).

6 The interaction with other risk management instruments needs to be mentioned here. Higher required capital also can be accounted for by changes in reinsurance, asset allocation, or underwriting strategy. In our analysis we control for such differences since these different strategies impact both inputs and outputs. For example, with more reinsurance, incurred losses are lower and less equity capital is needed.

7 If, for example, a proportional loading is added on the existing equity capital (e.g., every insurer has to hold 10% more equity), then efficiency remains unchanged. If a fixed loading is added (e.g., every insurer has to hold 1 million more equity), then efficiency could either increase or decrease.

bankruptcy should incentivize firms to operate efficiently. However, without solvency regulation there is potential for market failure, because insurers might act more risky than optimal from policyholders' view (Rees and Kessner, 1999). Because more risky activities increase insolvency risk and require more costly risk management activities efficiency losses might be the consequence. Additionally, in well-capitalized companies managers' interests should be more aligned with the shareholder interests which potentially increases efficiency (see e.g. Berger and Mester, 1997). Another argument that could be made is that in the long run increased security levels might result in an increased premium volume, because policyholders should value low levels of insolvency risk (see, e.g., Epermanis and Harrington, 2006).[8] These arguments imply a positive relation between solvency regulation and efficiency; this direction of relationship is also generally assumed in the banking literature (see e.g. Barth et al., 2013; Dietsch and Lozano-Vivas, 2000; Pasiouras, 2008). The existing empirical evidence for insurance markets (Eling and Luhnen, 2010; Luhnen, 2009) also confirms a positive relationship between solvency (equity to assets ratio) and the efficiency of global life insurers and German property-liability insurers, respectively.[9] We thus expect a positive relation between regulation (i.e. capital adequacy) and efficiency (Hypothesis H4).

Development over time and variations across countries

Next to these four main hypotheses we also consider the development of efficiency over time and the variations across countries; in this context we also analyze the development of total factor productivity.[10] The financial crisis has caused large differences in macro-economic

8 Wakker, Thaler and Tversky (1997) illustrate that an increase in insolvency risk drastically reduces the willingness to pay for insurance and thus premium volume. Vice versa, a decrease in insolvency risk might lead to an increase in premium volume.

9 The only study finding a negative link is Cummins and Nini (2002) which analyze capitalization of the U.S. property/liability insurance industry for the period 1993–1998 and find that most insurers significantly over-utilize equity capital. An over-utilization of equity capital leads to significant costs of capital, resulting in efficiency losses.

10 Productivity changes over time have been analyzed for various European countries: Focusing on productivity growth in five European insurance markets (Germany, France, Italy, Spain and the UK). Bertoni and Croce (2011) investigate productivity changes in life insurance for 1997-2004. They observe a significant Total

conditions among European countries. Whilst up to 2008 mostly all member countries were experiencing strong economic growth, conditions have diverged post-crisis with Southern countries being more seriously affected than Northern and Central European countries. Germany still benefitted from GDP growth after 2008 but mainly southern European countries recorded significant negative GDP growth. Structural unemployment in the European Union rose by more than 1 % between 2007 and 2013 and is overall about 2 % higher than the OECD average (OECD, 2014). Furthermore, unemployment varies significantly among the member countries with Germany (5 %) being at the bottom range and Spain (25 %) and Greece (27 %) marking the top range as of 2014 (European Commission, 2015). Furthermore, European markets experienced diverged interest rate developments. Whilst for France, Netherlands and Germany government bond spreads increased only relatively moderate post-crisis, countries such as Italy, Ireland and Spain suffered significant increases (see e.g. Barrios et al., 2009). Since life insurers are especially sensitive to interest rate changes (see e.g. Swiss Re, 2012) this development should have had varying impacts on European life insurers. Based on these outlined differences in the environmental conditions among European countries we expect an increased divergence in the efficiency after the financial crisis.

3. Methodology and Data

3.1. Methodology

The purpose of the empirical analysis is twofold. Firstly, we analyze the impact of the environmental conditions on technical and cost efficiency by regressing uncontrollable

Factor Productivity (TFP) increase of 6.71 % which is mostly due to technical innovation (+6.67 %) and only partly accounted for by technical adoption (+0.04 %). The latter indicates that, in the observed countries, more technical progress occurred by the best-practices firms, whereas the average insurer was not able to catch up. Hussels and Ward (2007) analyze German and UK life insurers for the period 1991 to 2002 and find small TFP growth (+2.7 %), which again is mainly accounted for by technical progress. Many other markets have been studied with regard to their TFP improvements for several time horizons mostly finding moderate productivity increase over time (see e.g. Cummins and Rubio-Misas, 2006 for Spain; Barros et al., 2005 for Portugal; Mahlberg and Url, 2003 and Ennsfellner et al., 2004 for Austria; Fecher et al., 1993 for France; Cummins, Turchetti, and Weiss, 1996 for Italy; and Bikker and van Leuvensteijn, 2008 for the Netherlands).

variables on efficiency scores.[11] This procedure allows hypothesis testing about the actual impact (significant or insignificant) and the effective direction (positive or negative) of the operating environment on European life insurer efficiency.

Secondly, we incorporate the operating environment in the measurement since in a cross-country setting efficiency results are biased towards different environmental conditions. We adapt the multi-stage DEA approach introduced by Fried et al. (1999)[12] and control for relatively favorable / bad conditions on a per-country as well as per-anno basis and obtain cross-country efficiency scores that fully reflect managerial efficiency. This is beneficial as it allows cross-country comparisons with all firms in the sample measured against the same benchmark. Simultaneously, the sample countries with the relatively least / most favorable operating environment during the sample period 2002 to 2013 are identified. Additionally, the procedure allows inferences whether the operating environment in the European life insurance sector overall had a beneficial (i.e. efficiency enhancing) or adverse impact.

The procedure requires four steps. The *first stage* constitutes a DEA with commonly used inputs and outputs. In the *second stage*, total input slacks are regressed against a set of uncontrollable variables representing the operating environment. In the *third stage*, initial input values, used in the first stage, are adjusted with respect to the impact of the environmental conditions on life insurer efficiency analyzed in the second stage. This step should benefit companies that operated in an unfavorable environment and penalize companies that took advantage of their environmental conditions. Finally, in the *fourth stage*, the DEA model is rerun on the basis of the adjusted input values from stage 3. The efficiency scores obtained in this stage should fully reflect managerial efficiency.

Before the four stages are explained in more detail the general DEA procedure is briefly

[11] A truncated regression procedure rather than a Tobit analysis is chosen since Simar and Wilson (2007) as well as McDonald (2009) show that Tobit regressions provide undesirable results in Monte Carlo experiments.

[12] Advantageous of the multi-stage approach is that various uncontrollable variables can be incorporated without

introduced as all parts of the empirical analysis in this paper draw on this efficiency measurement methodology. In the DEA best-practice firms are identified which determine the efficient frontier (Farrell, 1957). Firm efficiency of all other firms is measured relative to this frontier. We estimate input-oriented frontiers with constant returns to scale (CRS) to measure technical efficiency (TE) and variables returns to scale (VRS) to measure pure technical efficiency (PTE).[13] In addition, we measure scale efficiency (SE) and cost efficiency (CE). The allocation of efficiency scores to *N* decision making units (i.e. firms; DMUs) using *M* inputs to produce *K* outputs is illustrated by the following linear programming problem (Charnes et al., 1978).

$$TE_j = \min \theta_j$$

$$\text{s.t.} \quad \lambda_j X \leq \theta_j x_j$$

$$\lambda_j Y \geq y_j$$

$$\lambda_j \geq 0 \; (j = 1, 2, 3......N),$$

where TE represents Farrell's measure of technical efficiency for DMU j ($j = 1, 2, ...N$), X is a $M \times N$ matrix of all inputs used by *N* DMUs, Y is a $K \times N$ matrix of all outputs produced by *N* DMUs, *N* DMUs, x_j is a $M \times 1$ input vector for DMU j, y_j is a $K \times 1$ output vector and λ_j is an $N \times 1$ intensity vector of DMU j. In order to make efficiency scores of all life insurers in the 14 different countries comparable, we estimate cross-country frontiers. Therefore, life insurer's efficiency is measured relative to a European benchmark.[14] This approach, however, neglects that efficiency deviations could be also due to differences in the operating environments and not only due to differences in firm management. To analyze

a prio assumptions or understandings of their relation to the efficiency scores (see e.g. Yang and Pollitt, 2009).

13 We rely on the Simar and Wilson (2000) bootstrapping approach to estimate bias-corrected efficiency scores and therefore account for sample variations.

14 We thus assume that European insurance companies use the same set of technologies to produce their outputs. An approach for testing this assumption is cross-frontier analysis; see Biener and Eling (2012).

differences in the operating environment and comparing only pure managerial efficiency among European life insurers, we conduct the following four stages.

In the *first stage*, unadjusted inputs and outputs are considered (we call this Model 1), that is the efficiency scores represent both inefficiencies due to bad management and a bad operating environment. In the *second stage,* we determine total input slacks[15] and regress the outcome against a set of uncontrollable variables (i.e. the environmental conditions).[16] Following Fried et al. (2002) we use a stochastic frontier analysis (SFA) slack regression. Using the regression results we rerun the DEA model in the *third* and *fourth* stage (we call this Model 2). The SFA regression equation is specified as follows.[17]

$$S_{mj} = f^m(Z_j;\beta^m) + v_{mj} + u_{mj}$$

$$m=1, 2, \ldots\ldots, M;\ j=1,2,\ldots.., N,$$

where $S_{mj} = (rs_{mj} + nrs_{mj}) / x_{mj}$ are the percentages of total slacks[18] obtained from the *stage 1* in the usage of input m for DMU j. Z_j is a vector of uncontrollable variables for DMU j. β^m is a vector of coefficients. It is further assumed that v_{mj} (normally distributed with zero mean and variance σ^2_{vm}) reflects statistical noise and u_{mj} (half-normal distributed with variance σ^2_{um}) reflects managerial inefficiency. The estimation of the coefficients allows inferences about the contribution of the uncontrollable variables on input slacks.[19]

15 Total input slacks are obtained through summation of the radial $(rs_{mj} = x_{mj} - X_m\lambda)$ and non-radial slack (nrs_{mj}) components (see Fried et al. 1999). The calculation of the non-radial component requires a second linear programming which was carried out using the Benchmarking R package.

16 Through this procedure so-called allowable input slacks due to the operating environment can be obtained. The allowable input slacks mean that a certain amount of input waste is acceptable because it is caused by an adverse external environment and not by managerial inefficiency. The remaining (i.e. after controlling for the operating environment) input slacks represent management's excessive use of inputs.

17 Regarding the the functional form of f^m we follow Huang and Eling (2013) and assume a simple linear form. Note that we need SFA only for the second-stage regression and not for the determination of efficiency scores.

18 Because the magnitude of total slacks might correlate with the size of inputs, total slacks are given in percentages.

19 In addition to Model 2, we also estimate a Model 3 which considers statistical noise analogous to other regression models (i.e. the error term). Moreover, besides the contribution of uncontrollable variables and

In the *third stage*, the initial input values are adjusted upwards using the results from the second stage. The underlying rationale is that companies working under less favorable conditions need additional input quantities to produce the same level of output that companies under relatively more favorable conditions produce. Consequently, companies in less favorable operating environments yield lower efficiency scores merely due to adverse environmental impacts. To control for this, input quantities of companies working under more favorable conditions are adjusted upwards whilst keeping their output levels unadjusted. The scale of adjustment depends on how one operating environment stands in comparison to all other environments. This procedure is thus beneficial for companies that operate in an unfavorable environment and penalize companies that have good environmental conditions. The following equation shows the adjustment function which is the difference between maximum allowable slack among all life insurers and predicted (i.e. based on the model estimation) slack for one life insurer.[20]

$$x_{mj}^{A} = x_{mj}\left\{1+[\max_j\{f^m(z_j;\hat{\beta}^m)\} - f^m(z_j;\hat{\beta}^m)] + [\max_j\{\hat{v}_{mj}\} - \hat{v}_{mj}]\right\}$$

m=1, 2, ……, M; j=1,2,….., N,

where x_{mj}^{A} is adjusted and x_{mj} is original input data. Additionally, the adjustment function regulates for the difference between maximum statistical noise among all insurers and the one of insurer j. Therefore, Model 2 adjusts for the environment and statistical noise. The adjustment is conducted on an annual basis and is determined by taking the least favorable environment across all insurers, given as the maximum values of $f^m(z_j;\hat{\beta}^m)$ across all insurers, minus the environment of insurer j. Higher adjustments apply to insurers operating under more favorable conditions (with relatively low predicted slack) which will, ceteris

statistical noise model 3 also captures managerial inefficiency. A value close to zero for $\gamma^m = \sigma_{um}^2 / (\sigma_{um}^2 + \sigma_{vm}^2)$ indicates that deviations from the frontier are entirely due to statistical noise and a value close to one indicates that all deviations are due to managerial inefficiency. The results of Model 3 are available upon request.

paribus, lower their efficiency scores.[21] Consequently, we control for environmental impacts in the efficiency measurement; hence, making efficiency score comparable among the sample countries.

In the *fourth stage*, the DEA is rerun with the adjusted input values from stage 3. Because this model incorporate besides controllable (i.e. the management process) also uncontrollable variables (i.e. the operating environment) we attempt to control for the influence of environmental conditions on life insurer efficiency. Therefore, Model 2 reflects efficiencies that can be solely traced back to firm management and hence allow cross-country comparisons.

3.2. Data

Our sample includes all life insurers that are constitutes of the AM Best Insurance Reports data base and operate in Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Norway, Sweden, Switzerland and the United Kingdom in the sample period 2002–2013. Extreme data such as zero or negative total asset values were eliminated from the sample. For comparative purposes, all numbers were deflated to 2002 using ILO consumer price indices and converted into U.S. dollars using exchange rates obtained from AXCO Insurance Information Services.

Inputs and input prices

We follow the literature and use number of employees (x_1), debt capital (x_2), and equity capital (x_3) as inputs (see, e.g. Huang and Eling, 2013).[22] Since the number of employees is not available in the data we divide total operating expenses from the AM Best data base by country-specific prices of labor (as done in many other studies; see, e.g., Cummins et al., 2004; Fenn et al., 2008). The price of labor is obtained from the International Labor Organization

20 Yearly values of predicted slack are equal for all life insurers operating in the same country.

21 The idea of maximum predicted slack is to define a level of the least favorable set of external conditions. A life insurer operating in this environment would experience no adjustments of its input vector. A firm with uncontrollable variables generating a lower level of predicted slack would have its input vector adjusted upwards so as to put it on the same basis as the firm with the least favorable external environment. For more details, see Fried et al. (1999).

22 The definition of inputs, inputs prices and outputs is relatively standardized in the insurance literature. For this

(ILO; see http://laborsta.ilo.org/) which collects data on the average annual wages for either financial and insurance activities or financial intermediation activities. Since data is not available for every year we estimate missing values by linear interpolation. We use the price of labor as first input price (p_1), long-term interest rates (from the OECD) to proxy the price of debt (p_2) and the price of equity (p_3) is proxy by 15-year rolling returns on MSCI country-specific equity indices.[23]

Outputs

For the selection of outputs we follow Cummins and Weiss (2013) and use the value added-approach. The three services that insurers provide are risk pooling/bearing services, intermediation, and financial services. We use losses plus additions to reserves as the first output variable (y_1) and as a second output variable the total invested assets (y_2).[24]

Environmental (Uncontrollable) Variables

The selection process for the environmental variables is oriented at the banking literature (e.g., Dietsch and Lozano-Vivas, 2000; Lozano-Vivas et al., 2002; Fries and Taci, 2005; Liu and Tone, 2008) and the non-life insurance study of Huang and Eling (2013). Whenever appropriate, we make reasonable adaptions to the life insurance context. All variables are measured on a per-annum and per-country basis, that is, all life insurers operating in the same country have the same corresponding uncontrollable variable value in each year.

For the macro-economic conditions we follow Dietsch and Lozano-Vivas (2000) and proxy the economic performance by GDP per capita. We use OECD long-term interest rates as indicator for the interest rate level. Similar to Huang and Eling (2013) we include inflation and measure it by consumer price indices (basis: 2002 = 100).[25] Because life insurers are not only sensitive to interest rate levels, but also to equity market development we include rolling returns of

reason we do not discuss the economic rationale behind the variables in detail, but refer to other papers.

23 MSCI does not provide an index for Luxembourg; we thus use the MSCI Europe equity index for this country.

24 Both losses and total invested assets are highly correlated with the third service of insurers (financial services) and is thus generally not modeled as a separate output (see, e.g., Eling and Luhnen, 2010b).

25 Inflation affects insurer's operations such as pricing and reserving (see Ravin and Fowlds, 2010); also costs

country-specific MSCI indices to measure equity market performance. Finally, we consider the unemployment rate as adverse driver of life insurance demand. Increases in the unemployment rate are considered to decrease life insurance demand, especially in the context of lapse.[26]
Regarding industry-specific variables, we use the country average of equity to total assets to represent differences in capital requirements among countries (see e.g. Lozano-Vivas et al., 2002; Hussels and Ward, 2007). To measure competition we use the concentration ratio at the four-firm level (CR_4; see e.g. Huang and Eling, 2013). This measure is the sum of the market shares held by the four largest (in terms of gross written premiums) insurers in each country (see e.g., see Cummins et al., 2004; Fenn et al, 2008). Markets with high values of CR_4 are regarded as less competitive in comparison to markets with smaller CR_4 values. The premium data for the competition measure were obtained from Insurance Europe.

Firm Characteristics

In order to examine how firm-specific characteristics influence efficiency of European life insurers we also investigate selected firm factors in our second stage regressions. We focus on size, solvency and ownership. We measure ownership by binary variables where the value of 1 is allocated to stock companies and 0 to all others, size by the logarithm of total assets and solvency by the firm-specific ratio of equity to total assets. Different to the environment analysis, these variables vary across firms also within a specific country.

The final sample consists of 960 life insurers (6'657 firm years). Panel A of Table 2 presents an overview of the inputs, inputs prices, outputs, environmental variables and firm characteristics used in this analysis. Panel B of Table 2 shows summary statistics of this data set.

rise due to inflation (see Qaiser, 2006).

26 The two main lapse drivers in the life insurance industry are the interest rate and the unemployment rate (leading to the so called emergency fund hypothesis). See Eling and Kochanski (2013).

Table 2 Sample of European Life Insurers

Panel A: Definition of Controllable and Uncontrollable Variables

Controllable variables	*Inputs*	Labor	*x1*	1,000s	A.M. Best Operating expenses/ILO average annual wage
		Debt	*x2*	Mio. USD	A.M. Best total liabilities
		Equity capital	*x3*	Mio. USD	A. M. Best Capital and capital
	Outputs	Benefits + additions to reserves	*y1*	Mio. USD	A. M. Best net benefits + additions to reserves
		Investments	*y2*	Mio. USD	A. M. Best total invested assets
	Input prices	Price of labor	*p1*	USD	ILO average annual wage insurance and financial activities
		Price of debt capital	*p2*	%	OECD long-term interest rates
		Price of equity capital	*p3*	%	15y rolling returns on MSCI country-specific equity indices
Uncontrollable variables	*Macro-economic*	Economic performance	*GDP*	USD	Gross domestic product per capita
		Interest rate level	*IR*	%	OECD long-term interest rates
		Inflation	*INF*	%	THE WOLRD BANK Consumer price indices (year 2002 = 100)
		Equity market performance	*MSCI*	%	Rolling returns on MSCI country-specific equity indices
		Demand	*UNE*	%	AXCO unemployment rates
	Industry-specifics	Solvency	*SOLV*	%	Equity to total assets (country average)
		Competition	*COMP*	%	Concentration ratio at the four-firm level
Firm characteristics		Ownership	*OWN*	Dummy	(1= stock, 0=mutual)
		Size	*SIZE*	Mio. USD	Total assets
		Solvency	$SOLV_j$	%	Equity to total assets (firm specific)

Panel B: Summary Statistics *(mean values and standard deviations (in parenthesis))*

	Austria	Belgium	Denmark	Finland	France	Germany	Ireland	Italy	Luxembourg	Netherlands	Norway	Sweden	Switzerland	United Kingdom
x1	1.5131	0.2163	0.1036	0.9613	1.5719	1.6183	1.9412	5.5055	0.6802	4.0691	2.0590	2.3462	1.7268	7.1778
	(0.9738)	(0.2932)	(0.1899)	(1.7924)	(2.8726)	(3.64)	(2.5503)	(8.9569)	(1.1505)	(10.8993)	(2.2958)	(4.5571)	(3.2663)	(19.4139)
x2	2716137	804483.9	3998715	7488835	8563160	5732507	4266032	5827841	2666173	9712399	14700000	11000000	15200000	21500000
	(1914070)	(2365360)	(5366731)	(9173974)	(13200000)	(14400000)	(10500000)	(9035053)	(306627)	(19000000)	(15400000)	(12900000)	(29500000)	(44600000)
x3	61798	36575	434199	591436	369054	104044	218851	241819	50572	851812	1004411	4658862	631028	974427
	(47378)	(97309)	(508120)	(903494)	(526500)	(193961)	(413418)	(427167)	(34309)	(1764590)	(972787)	(7393884)	(1483274)	(1772556)
p1	54490	51305	104983	48633	61023	72225	48363	29165	81434	54108	83302	67321	109263	54732
	(17764)	(10007)	(20534)	(11253)	(12689)	(12516)	(12220)	(2245)	(21417)	(8640)	(28956)	(15087)	(22508)	(9196)
p2	0.0378	0.0394	0.0348512	0.0362	0.0378	0.0334	0.0483	0.0448	0.0359	0.0374	0.0379	0.0360	0.0218	0.0415
	(0.0079)	(0.0057)	(0.0108)	(0.009)	(0.0068)	(0.0096)	(0.0146)	(0.0056)	(0.0101)	(0.0081)	(0.0112)	(0.0101)	(0.008)	(0.009)
p3	0.0778	0.1026	0.1142417	0.1618	0.1133	0.0946	0.0492	0.0813	0.0674	0.1190	0.0803	0.1411	0.1231	0.0956
	(0.0140)	(0.014)	(0.0032)	(0.0152)	(0.012)	(0.0108)	(0.0144)	(0.0131)	(0.0058)	(0.0167)	(0.0065)	(0.0137)	(0.0085)	(0.0174)
y1	609832	295912	815231	2035098	1944007	1148108	1119935	1972864	924732	1622531	3358281	2096487	2724594	4884076
	(494994)	(1228506)	(1169217)	(2866080)	(3667684)	(3034686)	(2110567)	(3959638)	(120432)	(3310945)	(4391959)	(3275775)	(5203217)	(11100000)
y2	2573079	788309	4326531	7474697	8294342	5412775	3239427	5496521	2404162	9731777	15300000	15100000	14900000	19500000
	(1784103)	(2387994)	(5558504)	(8957435)	(12800000)	(13300000)	(6419357)	(8222692)	(288734)	(19200000)	(15900000)	(18300000)	(29000000)	(42300000)
GDP	40545	38312	51117	39912	36919	37516	47772	31384	90159	29067	80521	45563	60649	36511
	(7722)	(7471)	(8898)	(7294)	(6396)	(5920)	(7736)	(4757)	(21125)	(5457)	(19102)	(8618)	(14387)	(5018)
IR	0.0378	0.0394	0.0349	0.0362	0.0378	0.0334	0.0483	0.0448	0.0359	0.0374	0.0379	0.0360	0.0218	0.0415
	(0.0079)	(0.0057)	(0.0108)	(0.009)	(0.0068)	(0.0096)	(0.0146)	(0.0056)	(0.0101)	(0.0081)	(0.0112)	(0.0101)	(0.008)	(0.009)
INF	1.1034	1.1004	1.1119	1.0718	1.0904	1.0926	1.1252	1.1112	1.1164	1.1035	1.1236	1.0722	1.0440	1.1027
	(0.0800)	(0.0823)	(0.0812)	(0.0629)	(0.0616)	(0.0602)	(0.0733)	(0.0770)	(0.0869)	(0.0922)	(0.0733)	(0.0510)	(0.0273)	(0.1024)
MSCI	0.0778	0.1026	0.1143	0.1618	0.1132	0.0946	0.0492	0.0813	0.0674	0.1190	0.0803	0.1411	0.1231	0.0956
	(0.0140)	(0.0140)	(0.0033)	(0.0152)	(0.0120)	(0.0108)	(0.0144)	(0.0130)	(0.0058)	(0.0167)	(0.0065)	(0.0138)	(0.0085)	(0.0174)
UNE	0.0690	0.0793	0.0512	0.0826	0.0873	0.0856	0.0771	0.0807	0.0433	0.1285	0.0350	0.0696	0.0335	0.0594
	(0.0041)	(0.0042)	(0.0097)	(0.0069)	(0.0067)	(0.0186)	(0.0429)	(0.0123)	(0.0099)	(0.0409)	(0.0052)	(0.0116)	(0.0052)	(0.0130)
SOLV	0.0399	0.0805	0.1371	0.0785	0.0850	0.0875	0.1401	0.0659	0.0332	0.1116	0.0894	0.3022	0.0917	0.1137
	(0.0070)	(0.0213)	(0.0228)	(0.012)	(0.0131)	(0.0248)	(0.0313)	(0.0119)	(0.0044)	(0.014)	(0.0162)	(0.0572)	(0.0354)	(0.0243)
COMP	0.6136	0.6496	0.5064	0.8219	0.4800	0.4229	0.7102	0.5309	0.7201	0.6223	0.8422	0.5267	0.7194	0.3860
	(0.119)	(0.0289)	(0.0205)	(0.0274)	(0.0139)	(0.0152)	(0.0806)	(0.0417)	(0.1206)	(0.0454)	(0.0254)	(0.0714)	(0.0155)	(0.0472)
OWN	0.6667	0.8657	0.3615	0.5791	0.7861	0.5683	0.9016	0.8322	0.9302	0.8023	0.8621	0.6476	0.8235	0.8942
	(0.4787)	(0.3423)	(0.481)	(0.4945)	(0.4104)	(0.4954)	(0.2983)	(0.3741)	(0.2562)	(0.3987)	(0.3463)	(0.4788)	(0.3821)	(0.3077)
SIZE	3161158	909289	5092710	8782311	9914781	6429995	5083422	6749387	3103846	11900000	17800000	16900000	16700000	25900000
	(2306188)	(2567659)	(6723218)	(10800000)	(15300000)	(16200000)	(12300000)	(10300000)	(3689162)	(23800000)	(18900000)	(20700000)	(32800000)	(55900000)
$SOLV_j$	0.0328	0.0761	0.1355	0.0766	0.0822	0.0832	0.1346	0.0640	0.0339	0.1101	0.0834	0.3027	0.0711	0.0968
	(0.0253)	(0.071)	(0.0994)	(0.0562)	(0.1126)	(0.1557)	(0.1858)	(0.0876)	(0.0374)	(0.1004)	(0.0565)	(0.2308)	(0.0987)	(0.12)

4. Empirical Results

4.1. Efficiency Measurement

We first present the DEA results of Model 1 and Model 2 per country. The efficiency scores of Model 1 are based on unadjusted input values (stage 1). The efficiency scores of Model 2, on the contrary, reflect efficiency after controlling for the operating environment (i.e. using adjusting input values). Table 3 shows average and bias-corrected technical efficiency (TE), pure technical efficiency (PTE), scale efficiency (SE) and cost efficiency (CE) scores.

Table 3 DEA efficiency scores

	Model 1				**Model 2**				**Delta (Model 1 – Model 2)**			
Country	TE	PTE	SE	CE	TE	PTE	SE	CE	TE	PTE	SE	CE
Austria	0.94	0.94	1.00	0.53	0.89	0.90	1.00	0.51	-0.05	-0.04	0.00	-0.01
Belgium	0.90	0.90	1.00	0.59	0.86	0.87	0.99	0.57	-0.04	-0.03	0.00	-0.02
Denmark	0.97	0.98	1.00	0.72	0.94	0.96	0.99	0.70	-0.03	-0.02	-0.01	-0.02
Finland	0.94	0.95	0.99	0.69	0.87	0.89	0.98	0.64	-0.07	-0.06	-0.02	-0.04
France	0.90	0.91	0.99	0.66	0.86	0.88	0.97	0.63	-0.04	-0.03	-0.01	-0.03
Germany	0.93	0.94	0.99	0.59	0.90	0.91	0.99	0.56	-0.03	-0.03	-0.01	-0.02
Ireland	0.83	0.84	0.99	0.49	0.84	0.85	0.98	0.50	+0.01	+0.01	0.00	+0.01
Italy	0.91	0.92	1.00	0.56	0.89	0.90	0.99	0.57	-0.02	-0.01	-0.01	0.00
Luxembourg	0.92	0.92	1.00	0.66	0.87	0.87	1.00	0.61	-0.05	-0.05	0.00	-0.05
Netherlands	0.91	0.92	0.98	0.55	0.87	0.90	0.97	0.54	-0.04	-0.03	-0.01	-0.02
Norway	0.96	0.97	0.99	0.71	0.91	0.94	0.97	0.67	-0.05	-0.03	-0.02	-0.04
Sweden	0.95	0.96	0.99	0.50	0.92	0.95	0.97	0.47	-0.03	-0.02	-0.02	-0.03
Switzerland	0.92	0.93	0.99	0.55	0.85	0.88	0.97	0.49	-0.08	-0.06	-0.02	-0.07
United Kingdom	0.83	0.85	0.99	0.61	0.82	0.84	0.97	0.60	-0.02	0.00	-0.02	-0.01
Total Sample	0.91	0.92	0.99	0.60	0.88	0.90	0.98	0.58	-0.03	-0.02	-0.01	-0.02

Model 1 implicitly assumes that all companies operate under same environmental conditions. In this situation, technical efficiency (TE) is relatively high. The mean of TE, for example, across all countries and years is 0.91 showing that European life insurers on average could improve TE by 9 percentage points. For cost efficiency (CE) there is much more room for improvement. The average CE score is 0.60, meaning that there is on average 40 percentage points improvement potential.[27]

Regarding the variation across countries, Denmark has the highest efficiency value both in terms of TE and CE.[28] For example regarding TE, Denmark is 14 percentage points more efficient than Ireland, the least efficient country. Three other Northern European countries (Norway, Sweden, and Finland) follow Denmark in terms of TE. At the bottom range in terms of TE is Ireland and the United Kingdom.

Controlling for the operating environment rearranges the order of countries (see Model 2).[29] The largest decrease in TE can be observed for Switzerland, which illustrates that this country has the best environmental conditions (thus the highest adjustments).[30] Also Luxembourg, Finland and Norway have high adjustments revealing that these countries benefit from a good operating environment. Irish life insurers operated under the least favorable conditions (i.e. the delta is positive in conjunction with low input adjustments). This result might be explained by the fact that the economy of Ireland was severely affected by the financial crisis. Hence the efficiency of life insurers operating in this country should be underestimated in Model 1; Model 2 gives a more realistic picture of the actual managerial performance. The mean TE and CE scores for the total sample are marginally lower in Model 2 than in Model 1. This illustrates that controlling for the operating environment decreased the average efficiency of European life insurers. Overall, Denmark is still the most efficient country in terms of TE and CE.

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27 Model 1 PTE levels (vrs assumption) are on average (0.92) relatively equal to the average TE level (0.91) for the total sample. This is mirrored in an average SE score of 0.99 and thus European life insurers could only improve their size of operations by 1 % to become fully scale efficient. In Model 2 the average PTE level is 0.2 higher than the average TE (0.88) value. Therefore, under homogenous environmental conditions there is room for improving SE by 1 %.

28 The finding that Denmark has the highest average efficiency levels across European countries is in line with Eling and Luhnen (2010) who analyze insurer efficiency in 36 countries including all countries that are included in our sample (their sample additionally comprises Spain, Poland and Portugal).

29 Table A2 in the Appendix summarizes the input adjustments (stage 3) with respect to the slack regression results. The slack regression results (stage 2) are presented in Table A1 in the Appendix.

30 Correspondingly to the delta, the adjustments of the input quantities (Table A2 in the appendix) could be considered. Here countries with higher adjustments operated under more favorable conditions in comparison to all other countries and countries with lower input adjustments operated under less favorable conditions. This procedure identifies the same countries in terms of best or worst operating environment.

4.2. Regression Analysis

In Table 4 we investigate the relationship between the efficiency scores of Model 1 (unadjusted) and Model 2 (adjusted) as dependent variables and the environmental variables and firm characteristics.

Table 4 Regression Results

			Model 1		**Model 2**	
	Variable	Definition	TE	CE	TE	CE
Panel A: Regression of environmental conditions						
Macro-economic						
Economic performance	*GDP*	ln(GDP per capita)	0.0061 (0.0116)	0.1303*** (0.0192)		
Interest rate level	*IR*	Long-term interest rates	-1.7394*** (0.2500)	3.1815*** (0.4194)		
Inflation	INF	Consumer price indices (2002=100)	-0.3843*** (0.0652)	0.5606*** (0.1266)		
Equity market performance	MSCI	Rolling returns on MSCI indices	0.2877*** (0.0854)	1.8062*** (0.1434)		
Demand	*UNE*	Unemployment rate	0.0588 (0.0756)	-0.5140*** (0.1270)		
Industry-specifics						
Capital requirements	*SOLV*	Equity to total assets (country-average)	-0.0056 (0.0363)	-0.3914*** (0.0622)		
Competition	*COMP*	Concentration ratio 4-firm-level	0.0312** (0.0144)	-0.1358*** (0.0240)		
Sigma			0.1242*** (0.0011)	0.2208*** (0.0020)		
Panel B: Regression of firm characteristics						
Organizational form	*OWN*	Dummy (1= stock, 0=mutual)	-0.0458*** (0.0035)	-0.1371*** (0.0060)	-0.0478*** (0.0036)	-0.1163*** (0.0057)
Size	*SIZE*	ln(Total assets)	0.0017** (0.0008)	0.0245*** (0.0014)	0.0019** (0.0008)	0.0275*** (0.0014)
Solvency	$SOLV_j$	Equity to total assets (firm-specific)	-0.0766*** (0.0126)	-0.5393*** (0.0203)	0.0016 (0.0120)	-0.4636*** (0.0245)
Sigma			0.1269*** (0.0012)	0.2019*** (0.0021)	0.1225*** (0.0011)	0.2109*** (0.0020)
Year dummies included			Yes	Yes	Yes	Yes
Number of observations			6657	6657	6657	6657

Note: *** (**, *) represents significance at the 1 % (5 %, 10 %) level; the numbers in parentheses are standard errors

Economic performance: We proxy the economic performance by GDP per capita and expect a positive relation to efficiency (hypothesis H1). Table 4 confirms this expectation for cost efficiency supporting H1. European life insurers seem to enhance CE when GDP per capita increases; thus more mature insurance markets incentivize firms to find more cost-optimal input combinations in order to remain competitive. For TE, however, the coefficient is insignificant. We can thus support H1 only for CE.

Interest rate level: The expected negative relation between the interest rate level and efficiency (hypothesis H2) is revealed for technical efficiency. European life insurers are encouraged to operate more efficiently in lower interest rate environments, probably to compensate for lower interest income and to adapt to the difficult business environment. Different to TE, the CE coefficient is positive and significant. This might be explained by the fact that interest rates determines the price of debt; with declining interest rate the costs of production and thus productivity decreases, while the impact on efficiency is negative in general.[31] An interest rate increase thus has a negative impact on TE, but encourage firms to choose more cost-optimal input combinations because the costs of production increase. Therefore, we can support H2 only for TE.

Competition: Following empirical results for the life insurance industry we expect a positive relation between competition and efficiency. This expectation implies a negative coefficient for COMP since increases in COMP go along with the assumption of competition losses. Table 4 reveals divergent impacts on TE and CE. The coefficient of COMP is positive and significant for TE. Hence increases in COMP have a positive impact on TE. Taking the summary statistics (Table 2) and the efficiency results (Table 3) into account shows that especially countries with high levels of COMP such as Norway, Finland and Switzerland have also high technical efficiency levels. The result for TE does not confirm our hypothesis H3 but rather endorses Demsetz' efficient market structure hypothesis. If Demsetz' theory holds true we should find a positive coefficient of COMP also for CE. The coefficient is insignificant though. Therefore, the results do not confirm either theory.

Regulation (Capital Adequacy): We use the country average of equity to total assets to analyze

[31] If, for example, interest rates decline by 100 basis points, the costs of production decreases by a fixed amount and thus productivity increases. If the output is unaffected, the efficiency (relative productivity between the companies) might either increase or decrease. See note 7 for the same discussion in a different context.

differences in capital requirements. Based on a theoretical discussion and in line with empirical evidence for the life insurance sector we expect a positive relation between capital requirements and efficiency. For TE we cannot confirm that changes in SOLV have an impact though; the coefficient is insignificant. For CE we find a negative relation. This relation could be explained by that higher capital requirements induce life insurers to hold more costly equity capital which constrains companies finding cost-optimal input combinations. It also might indicate that life insurers are over-utilizing capital as suggested by Cummins and Nini (2002) for the U.S. property/liability insurance industry. An over-utilization of equity capital might result in significant revenue and cost of capital penalties, resulting in efficiency losses. Therefore, capital requirements seem to be a constraint for life insurers to choose optimal input combinations from a cost point of view. Overall, we cannot find empirical evidence supporting our hypothesis H4.

The *other macro-economic conditions* for which we do not formulate own hypotheses show the following: For inflation (INF), measured by consumer price indices, we the same relation as for the interest rate level (negative with TE; positive with CE). Since inflation should increase input prices (e.g. price of labor; p1) life insures seem to be encouraged to increase CE by finding more optimal input-combinations just like in case of the interest rate level. Our measure for the equity market performance (MSCI) is the only macro-economic variable where we find a positive relation with both TE and CE. The demand factor UNE (measured by the unemployment rate) has to be interpreted in the following way. Increases in UNE go along with the expectation of lower life insurance demand and decreases in UNE vis-versa. Table 4 reveals a negative coefficient of UNE for CE. Hence, we infer that increases in life insurance demand, represented by a decrease in UNE, have a positive impact on CE. Life insurers seem to be encouraged to find cost-minimal input combinations; costs advantages could then be passed to potential customers. For TE, we cannot infer that life insurance demand has an impact.

Considering the *firm characteristics*, Table 4 documents that mutual life insurers are both more technical and more cost efficient than stock life insurers. This conclusion holds true also after controlling for the operating environment (Model 2).[32] Furthermore, Table 4 shows that increases in size have a positive impact on TE and CE for both Model 1 and Model 2. Therefore, we conclude that size expansions tend to increase TE and CE under homogenous and heterogeneous conditions.[33] For our solvency measure (SOLV) we find a negative relation to TE and CE when the operating environment is neglected (Model 1). After controlling for the operating environment (Model 2), however, we cannot confirm this relation for TE anymore. Increases in SOLV still decrease CE though. Again this result emphasizes the cost of capital penalties already documented in Cummins and Nini (2002).

4.3. Development of Productivity and Efficiency over Time

In this section, we show how productivity and efficiency develop under heterogeneous environmental conditions (Model 1) and under homogenous conditions (Model 2). Figure 1 presents yearly average TE scores for the total sample and depicts the development of efficiency in the European life insurance sector over the sample period.

Figure 1 Development of Efficiency Over Time

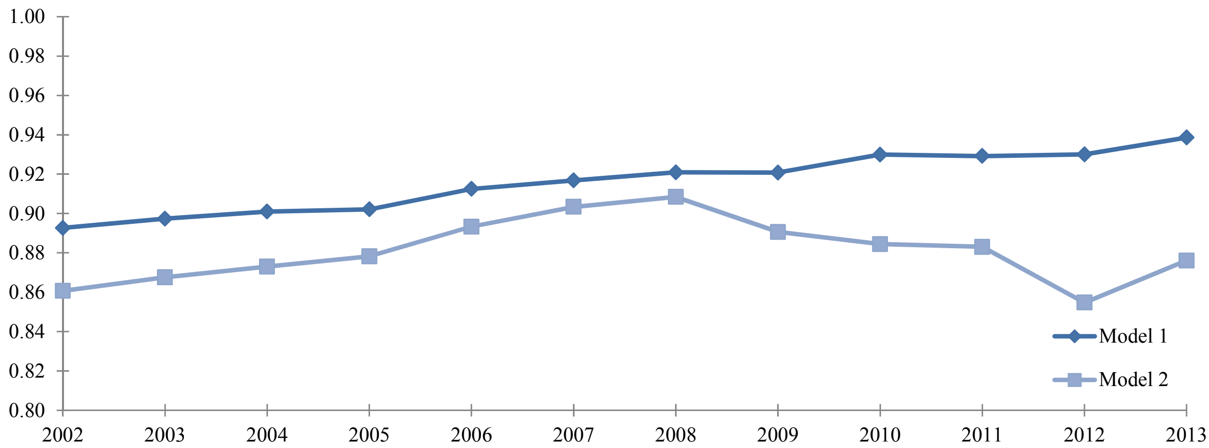

Figure 1 illustrates that average efficiency in European life insurance increases over the sample period (Model 1). Increasingly different operating environments placing more pressure on life

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[32] More empirical analyses is needed to derive firm conclusions on this topic, but our general finding that mutual are better than stocks is in line with Biener et al. (2015) for the Swiss life insurance market, Luhnen (2009) for the German non-life market and Biener and Eling (2012) for the European and U.S. life and non-life markets. The results do not confirm the expense preference hypothesis, but might provide some indication for the managerial discretion hypothesis. For a detailed discussion of these hypotheses we refer to Biener and Eling (2012).

[33] Many frontier efficiency studies in insurance have found a positive relationship between size and efficiency,

insurers could explain the efficiency progress. Furthermore, the development of Model 2 shows that in the pre-crisis period 2002-2008 operating environments converged in the sample (Model 2 TE levels approach Model 1 efficiency levels). After 2008, however, differences between Model 1 and Model 2 become larger. Figure A1 (Appendix) shows average input adjustments p.a. over the sample period. This reveals that post financial crisis countries were differently affected by the operating environment causing higher input adjustments.[34] Overall, we can confirm our expectation of increased divergence in efficiency post financial crisis.

We also analyze total factor productivity (TFP) changes by estimating input-oriented Malmquist productivity indices. Table 5 presents average annually TFP changes and TFP changes for the complete sample period (average TFP changes per annum and per country are given in Table A3 in the appendix).[35] TFP changes are further decomposed into technical, technical efficiency, pure technical efficiency and scale efficiency changes. The results are presented separately for Model 1 and Model 2.

Table 5 Malmquist Index of Total Factor Productivity

Period	**Average No. Of firms**	**Technical change**	**Technical efficiency change**	**Pure technical efficiency change**	**Scale efficiency change**	**TFP change**
Model 1: Undajusted						
Annual change (arithmetic mean)	479	1.00	1.00	1.00	1.00	1.00
Annual change (geometric mean)	479	1.00	1.00	1.00	1.00	0.99
Sample period: 2002 - 2013	219	1.00	0.98***	0.98**	1.00	0.98**
Model 2: Adjusted for the environment						
Annual change (arithmetic mean)	479	1.00	1.00	1.00	1.00	1.00
Annual change (geometric mean)	479	1.00	1.00	1.00	1.00	1.00
Sample period: 2002 - 2013	219	1.01	1.02***	1.00	1.01	1.02***

Note: Test of significance is based on two-tailed t-test using the bootstrapped Malmquist indices. : *** (**, *) represent significant differences from unity at the 1% (5%, 10%) level

For Model 1 we do not find significant annual TFP changes when we only consider samples of

e.g. because of economies of scale; see e.g., Cummins and Rubio-Misas (2006) or Luhnen (2009).

34 If only one country experiences comparatively bad environmental conditions (all other countries operate under equal conditions) all other countries would be penalized with the same proportional input adjustment. The net effect on efficiency for the total sample should be marginal in this case. If the environmental conditions across all countries vary input adjustments are not proportional and countries are penalized differently. In our sample this causes a significant reduction in the efficiency level.

35 The annual average values were calculated based on samples of firms that were present in every adjacent

firms that were present in every adjacent two-year periods between 2002 and 2013. If we consider the total sample period we see a significant TFP decline of approximately 2 %. This development documents that European life insures lost productivity. The decomposition of the Malmquist index reveals that this productivity loss stems from negative technical efficiency changes. Therefore, whilst the frontier did not shift (technical change is insignificant) European life insurers on average moved away from the frontier. One potential explanation for this is that under the given environmental conditions it has become more difficult for average life insurers to produce given levels of output with equal or lower levels of inputs. For example, increased capital requirements for investment risks accordingly caused higher levels of equity inputs, though producing equal levels of output. Consequently, productivity declined over time under heterogeneous environmental conditions.[36]

If we, however, control for the different environmental conditions across the sample, Table 5 reveals that productivity increased by roughly 2 % over the sample period (Model 2). Different to Model 1, average life insurers were able in Model 2 to move closer to the frontier. It thus seems that European life insurance managers took great efforts to improve the factor productivity, but the managerial improvement in total factor productivity was overcompensated by a negative effect due to the worsening environmental conditions. This again illustrates that European life insurers are under pressure due to the challenging changes in their operating environment. The results also again emphasize the importance of decomposing productivity and efficiency changes into environmental and managerial effects.

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two-year periods. The average values for the complete sample period were calculated based on a sample of firms that operated in every year.

[36] These results mirror the country-specific findings of Biener, Eling and Wirfs (2015) for Swiss life insurers and Cummins and Rubio-Misas (2006) for the Spanish life and non-life insurance industry. Cummins and Rubio-Misas (2006) argue that the costs of adjusting to a new regulatory environment might lead to a slippage in the production frontier. Especially for life insurance, they note that technical regress could also occur because of an increase in the output quality, e.g., associated with the increasing importance of asset allocation products in life insurance, which require a higher level of technology investment to provide competitive services. Biener, Eling and Wirfs (2015) argue that the findings illustrate the general difficulties experienced by the life insurance sector in adapting to an increasingly challenging business environment of low interest rates and increased competition from other financial service providers, such as banks. While the level of inputs remains largely unchanged, in many cases the output levels decline, for instance due to the loss of business to competitors in other industries or due to lower investments.

5. Conclusions

We analyze the impact of environmental conditions on productivity and efficiency of European life insurance companies using multi-stage Data Envelopment Analysis. This approach allows distinguishing environmental changes and changes in management practices. We also identify environmental conditions and firm-specific drivers of efficiency in a second stage regression analysis following Simar and Wilson (2007).

Our results show that capital markets (interest rates, equity market returns) and inflation are important drivers of life insurers efficiency. Secondly, we document that larger companies and mutual insurers have higher efficiency. Thirdly, we show that productivity declines and efficiency increases – a result which illustrates the difficulties of the whole European life insurance sector to adapt to the increasingly difficult business environment. The findings have implications for insurance managers, regulators and policymakers: they show that the life insurance industry is increasingly under pressure and that bad internal performance (underwriting practices, cost management) can no longer be compensated by a good environmental situation (such as e.g. high capital market returns). The findings thus help to validate and better understand the determinants of productivity and efficiency in the insurance sector. The results also indicate that some life insurers are over-utilizing equity capital, a finding which might be important for the appropriate definition of risk-based capital standards by regulators.

The analysis presented here also opens room for future research in various directions. For example, on the methodological side other types of efficiency (e.g., revenue efficiency, profit efficiency), other types of adjustments (e.g., conditional mean approach used in stochastic frontier analysis) and other types of relationships (e.g., non-linear link between GDP and efficiency as indicated by the s-curve; see Enz, 2000) could be analyzed. Cross-frontier analysis (Biener and Eling, 2012) could be used to further validate how different the operating environments are, 20 years after the liberalization of the European marketplace. Regarding the industry and geographical coverage, the European non-life sector has not yet been considered in the context of multi-stage DEA. Also since the economic and regulatory developments discussed in this paper are a global phenomenon, it would be interesting to analyze how the life insurance industry outside Europe (North-America, Asian markets) handles the increasingly difficult business environment.

Appendix

Table A1 Slack regression results

	Variable	Definition	**Slack1** Labor	**Slack 2** Debt	**Slack 3** Equity
Environmental conditions					
Macro-enomic					
Economic performance	*GDP*	ln(GDP per capita)	-0.300*** (0.0247)	-0.048*** (0.0092)	-0.049*** (0.0093)
Interest rate level	*IR*	Long-term interest rates	0.03041046* (0.0164)	0.047798*** (0.0059)	0.04978428*** (0.0059)
Inflation	*INF*	Consumer price indices (2002=100)	0.709*** (0.1022)	0.013 (0.0366)	0.017 (0.0369)
Equity market performance	*MSCI*	Rolling returns on MSCI indices	-0.265*** (0.0184)	-0.060*** (0.0066)	-0.063*** (0.0066)
Demand	*UNE*	Unemployment rate	0.048*** (0.0156)	-0.016*** (0.0056)	-0.020*** (0.0057)
Industry-specific					
Capital requirements	*SOLV*	Equity to total assets	-0.078*** (0.0116)	0.018*** (0.0042)	0.019*** (0.0042)
Competition	*COMP*	Concentration ratio 4-firm-level	0.079*** (0.0196)	-0.004 (0.007)	-0.003 (0.0071)
Log likelihood function			-2602.72	4253.74	4217.92
Sigma_v			0.128	0.016	0.016
γ^m			0.00068	0.00001	0.00002

Note: *** (**, *) represents significance at the 1 % (5 %, 10 %) level; the numbers in parentheses are standard errors

Table A2 Summary Statistics of Adjusted Input Data

	Input 1 Labor					**Input 2** Debt					**Input 3** Equity capital				
	Mean	STD	Min	Max	Adjust-ment	Mean	STD	Min	Max	Adjust-ment	Mean	STD	Min	Max	Adjust-ment
Austria	1.7370	1.1121	0.0748	3.8617	15 %	2930679	2081342	224046	5753747	08 %	67131	52530	10460	198148	09 %
Belgium	0.2659	0.3598	0.0044	1.5857	23 %	863135	2526946	5053	19200000	07 %	39315	104242	588	696384	07 %
Denmark	0.1573	0.2801	0.0015	2.3385	52 %	4418214	6019551	1623	34400000	10 %	477076	563476	1480	2970132	10 %
Finland	1.3616	2.3496	0.0154	23.7166	42 %	8374750	10300000	21363	41300000	12 %	659220	995710	596	5036277	11 %
France	2.0804	3.8161	0.0031	22.8304	32 %	9289605	14400000	1458	93900000	08 %	401792	575431	1735	3972288	09 %
Germany	2.0886	4.7504	0.0000	77.3875	29 %	6197613	15600000	131	219000000	08 %	113141	211885	296	2361902	09 %
Ireland	2.1786	2.8901	0.0032	20.4180	12 %	4314892	10600000	3477	97100000	01 %	221162	416883	1524	3297199	01 %
Italy	5.9728	9.5795	0.0046	60.3156	08 %	6087366	9431208	6812	67500000	04 %	253362	447582	5118	3485363	05 %
Luxembourg	0.9152	1.5196	0.0879	9.7524	35 %	2964363	3515622	363726	25200000	11 %	56127	39172	7993	190751	11 %
Netherlands	4.8967	12.8578	0.0035	101.6752	20 %	10400000	20400000	2394	92700000	07 %	917442	1906777	336	11600000	08 %
Norway	3.0458	3.3363	0.0004	14.9117	48 %	16100000	17000000	7713	62000000	10 %	1099352	1073010	4719	3626772	09 %
Sweden	3.5968	6.7948	0.0002	48.1742	53 %	11900000	14100000	71	70200000	08 %	5082182	8080594	730	29700000	09 %
Switzerland	2.7588	5.0288	0.0044	41.3438	60 %	17400000	34300000	1242	202000000	14 %	731099	1749427	4135	12700000	16 %
United Kingdom	9.5389	26.3618	0.0003	318.4361	33 %	22700000	47400000	2146	422000000	06 %	1030661	1882445	893	14500000	06 %
Total sample	3.2384	10.7156	0.0000	318.4361	28 %	8996787	22200000	71	422000000	8 %	562540	1986452	296	29700000	08 %

Figure A1 Average Input Adjustments p.a.

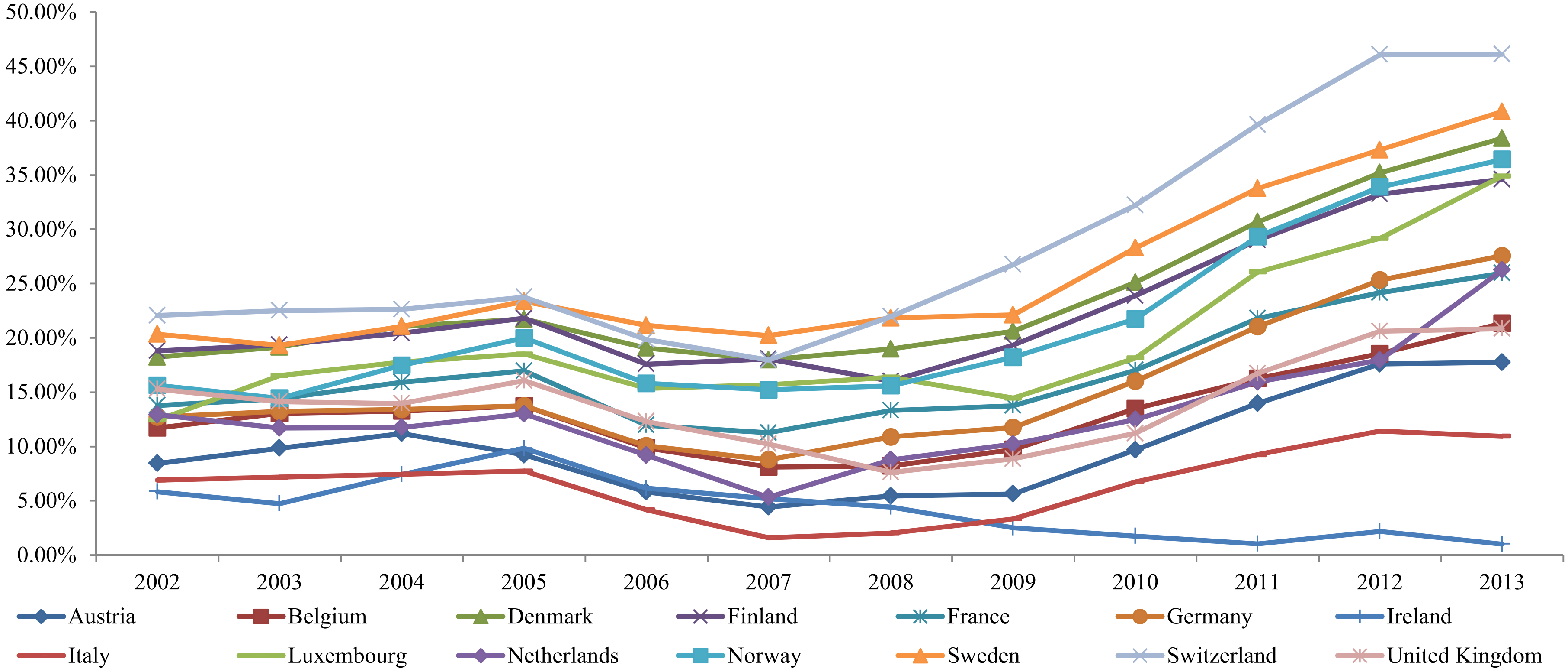

Table A3 Productivity over time

Year	2002/2003			2003/2004			2004/2005			2005/2006			2006/2007			2007/2008			2008/2009			2009/2010			2010/2011			2011/2012			2012/2013			2002/2013		
Model 1	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP
Austria	0.97	1.00	0.97	1.02	1.00	1.02	0.99	1.00	0.99	0.99	1.00	0.99	0.99	1.00	0.99	1.00	1.00	1.00	0.99	1.00	0.99	1.00	1.00	1.00	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.93	1.00	0.93
Belgium	1.00	0.97	0.97	1.00	1.00	1.00	0.98	1.00	0.98	1.00	1.00	1.00	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.03	1.01	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.99	0.95	1.00	0.95
Denmark	1.02	0.98	1.00	0.99	1.00	0.99	0.99	1.01	1.00	1.00	1.00	1.00	0.99	1.00	0.99	1.01	1.01	1.02	1.00	0.99	0.99	0.99	1.00	0.98	1.00	1.03	1.03	1.00	0.99	0.98	0.99	1.03	1.02	0.98	1.00	0.98
Finland	1.00	0.99	0.99	0.99	1.00	0.99	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.02	0.98	1.00	0.98	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.99	0.98	1.03	1.01
France	1.00	1.00	0.99	0.99	1.00	0.99	0.98	1.00	0.98	0.98	1.00	0.98	1.00	1.00	1.00	0.99	1.02	1.00	0.99	0.99	0.98	0.99	1.00	0.99	1.00	1.00	1.00	1.03	0.98	0.99	0.99	1.00	1.00	0.98	1.00	0.98
Germany	1.01	0.99	0.99	0.99	1.00	1.00	0.98	1.01	0.99	0.99	1.00	0.99	0.99	1.00	0.99	1.00	1.03	1.03	1.00	0.99	0.99	1.00	1.04	1.03	1.00	1.00	0.99	1.00	1.00	1.00	0.99	1.01	1.00	0.96	1.00	0.96
Ireland	1.02	0.94	0.96	1.01	0.99	1.01	1.01	1.00	1.01	1.07	1.00	1.07	1.02	1.00	1.02	1.08	1.08	1.14	1.07	0.97	1.02	0.98	1.03	1.01	1.01	0.98	0.99	0.99	1.02	1.01	0.99	1.00	1.00	1.09	1.00	1.09
Italy	0.99	0.99	0.98	0.99	1.00	0.99	0.99	1.00	0.99	1.01	1.00	1.01	1.01	1.00	1.01	1.00	1.00	1.00	0.98	1.00	0.98	1.00	1.01	1.01	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.06	1.03
Luxembourg	0.99	0.99	0.98	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.99	1.00	1.00	1.00	1.02	1.00	1.02	1.29	0.97	1.26	1.06	1.05	1.11	0.94	1.05	0.99	0.95	0.97	0.93	1.00	1.06	1.06	0.97	0.97	0.94
Netherlands	1.00	0.99	0.99	0.99	1.00	0.99	0.97	1.00	0.97	0.98	1.00	0.98	1.00	1.00	1.00	1.02	1.00	1.02	0.99	1.00	0.99	0.99	1.00	0.99	1.00	1.00	1.00	0.99	1.00	0.99	1.00	1.00	1.00	0.96	1.00	0.96
Norway	0.99	1.00	0.99	0.98	1.00	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.01	0.91	1.01	0.92	0.97	1.00	0.97	1.00	1.00	1.00	1.01	1.03	1.04	1.00	1.00	1.00	1.00	1.01	1.01	0.98	1.00	0.98
Sweden	0.99	1.00	0.99	1.01	1.00	1.01	0.98	0.99	0.97	0.99	1.00	0.99	1.00	0.99	0.99	0.98	1.13	1.10	1.00	1.01	1.01	1.03	1.01	1.03	1.02	1.00	1.02	1.01	1.00	1.00	0.99	1.00	1.00	0.99	1.00	0.99
Switzerland	1.00	0.99	0.99	1.01	0.99	1.00	1.23	0.97	1.12	0.95	0.99	0.94	1.11	1.00	1.12	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.02	1.01	1.00	0.98	0.99	0.99	1.00	0.99	1.00	1.00	1.00	0.97	1.00	0.97
United Kingdom	1.00	0.95	0.95	0.99	1.01	1.00	0.99	1.00	1.00	1.01	1.00	1.00	0.99	1.01	1.00	0.91	1.04	0.95	0.99	1.00	0.99	1.00	1.00	1.00	1.02	1.00	1.02	1.01	0.96	0.97	1.00	1.03	1.03	1.03	0.97	1.01
Total Sample	1.00	0.98	0.98	1.00	1.00	1.00	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.03	1.03	1.00	0.99	0.99	0.99	1.02	1.01	1.00	1.00	1.00	1.00	0.99	0.99	1.00	1.01	1.01	0.98	1.00	0.98
Model 2	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP
Austria	0.97	1.00	0.97	1.02	0.99	1.01	0.98	1.00	0.98	0.99	1.00	0.99	0.98	1.00	0.98	0.99	1.02	1.01	1.02	0.98	0.99	1.02	1.01	1.04	1.01	1.02	1.03	1.01	0.99	1.00	1.00	1.01	1.00	0.96	1.00	0.96
Belgium	0.99	0.96	0.95	1.01	0.99	1.01	0.98	1.00	0.98	0.99	1.00	0.99	0.99	1.00	0.99	1.00	1.01	1.01	1.02	0.99	1.01	0.99	1.04	1.03	0.99	1.04	1.03	1.04	0.96	1.00	0.97	1.01	0.98	0.96	1.01	0.96
Denmark	1.02	0.98	0.99	0.99	0.98	0.97	0.99	1.01	1.00	0.99	0.99	0.99	0.99	0.99	0.98	1.01	1.03	1.04	1.01	0.99	1.00	1.00	1.02	1.02	1.00	1.07	1.07	1.04	0.97	1.00	0.99	1.01	1.00	1.02	1.00	1.02
Finland	0.99	0.98	0.97	0.99	0.99	0.98	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.02	1.02	1.03	1.00	0.98	0.98	1.01	1.00	1.02	0.98	1.05	1.03	1.06	0.95	1.01	0.97	1.02	0.98	1.03	1.02	1.05
France	1.00	0.99	0.98	0.99	0.99	0.98	0.98	1.00	0.98	0.98	0.99	0.97	0.99	1.00	0.99	0.98	1.03	1.01	1.03	0.97	1.00	1.01	1.01	1.02	0.99	1.04	1.03	1.06	0.95	0.99	0.98	1.02	0.99	1.03	0.99	1.02
Germany	1.01	0.98	0.99	0.99	1.00	0.99	0.98	1.01	0.99	0.98	1.00	0.98	0.99	0.99	0.98	1.00	1.04	1.05	1.02	0.98	1.00	1.01	1.05	1.06	1.00	1.03	1.03	1.04	0.98	1.01	0.97	1.02	0.98	1.01	1.01	1.02
Ireland	1.02	0.93	0.95	1.02	0.98	1.00	1.01	1.01	1.02	1.07	1.00	1.07	1.02	1.00	1.02	1.07	1.09	1.14	1.07	0.97	1.02	0.98	1.05	1.02	1.01	0.98	0.99	0.99	1.02	1.02	0.99	1.02	1.01	1.07	1.01	1.08
Italy	0.99	0.98	0.96	0.99	0.99	0.98	0.99	1.00	0.99	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.01	1.01	1.00	0.99	0.99	1.02	1.01	1.03	1.03	1.01	1.03	0.99	1.00	0.98	0.99	1.01	1.00	0.97	1.07	1.04
Luxembourg	1.01	0.98	0.98	1.01	0.99	1.00	1.00	1.00	1.00	0.99	1.00	0.98	0.99	1.00	0.99	1.01	1.02	1.03	1.30	0.95	1.25	1.08	1.08	1.15	0.97	1.08	1.05	1.00	0.95	0.94	0.96	1.13	1.09	0.98	0.99	0.97
Netherlands	1.00	0.98	0.98	0.99	0.99	0.98	0.97	1.00	0.97	0.97	1.00	0.97	0.99	1.00	0.99	1.02	1.01	1.03	1.01	0.99	0.99	1.00	1.01	1.01	1.01	1.02	1.03	1.01	0.99	1.00	0.99	1.01	1.01	0.98	1.00	0.98
Norway	1.00	0.99	0.99	0.99	0.99	0.98	0.99	1.00	0.99	0.99	1.00	0.98	1.00	1.00	1.00	0.93	1.01	0.94	1.00	0.98	0.98	1.02	1.01	1.04	1.02	1.07	1.08	1.04	0.97	1.01	0.98	1.01	0.99	1.04	0.99	1.03
Sweden	0.99	1.00	0.99	1.00	0.99	1.00	0.98	0.99	0.97	0.98	0.99	0.98	0.99	0.99	0.98	0.98	1.12	1.10	1.01	1.00	1.01	1.04	1.03	1.07	1.04	1.02	1.06	1.04	0.98	1.02	0.95	1.02	0.97	0.99	1.02	1.01
Switzerland	1.01	0.98	0.99	1.00	0.99	0.99	1.22	0.97	1.12	0.94	0.98	0.93	1.10	1.00	1.11	0.99	1.01	1.00	1.04	0.98	1.02	1.02	1.03	1.05	1.01	1.02	1.02	1.05	0.97	1.02	0.96	1.02	0.97	1.03	1.00	1.03
United Kingdom	0.99	0.94	0.94	0.99	1.00	0.99	0.98	1.00	0.99	1.00	0.99	0.99	0.99	1.01	1.00	0.91	1.05	0.96	1.01	0.99	1.00	1.02	1.01	1.03	1.02	1.03	1.05	1.03	0.95	0.99	0.96	1.04	1.00	1.03	0.99	1.02
Total Sample	1.00	0.97	0.97	0.99	0.99	0.99	0.99	1.00	0.99	0.99	1.00	0.99	1.00	1.00	0.99	1.00	1.04	1.04	1.02	0.98	1.01	1.01	1.03	1.04	1.00	1.03	1.03	1.03	0.97	1.01	0.97	1.02	0.99	1.02	1.01	1.02

Note: TEC stands for Technical Efficiency Change, TC stands for Technical Change, TFP stands for Total Factor productivity

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